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Visualization of internal defects using a deep generative neural network model and ultrasonic nondestructive testing

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Introduction. The development of machine learning methods has given a new impulse to solving inverse problems in mechanics. Many studies show that along with well-behaved techniques of ultrasonic, magnetic, and thermal nondestructive testing, the latest methods are used, including those based on neural network models. In this paper, we demonstrate the potential application of machine learning methods in the problem of two-dimensional ultrasound imaging.

Materials and Methods. We have developed an experimental model of acoustic ultrasonic non-destructive testing, in which the probing of the object under study takes place, followed by the recording of the response signals. The propagation of an ultrasonic wave is modeled by the finite difference method in the time domain. An ultrasonic signal received at the internal points of the control object is applied to the input of the convolutional neural network. At the output, an image that visualizes the internal defect is generated.

Results. In the course of the performed complex of numerical experiments, a data set was generated for training a convolutional neural network. A convolutional neural network model, which is developed to solve the problem of visualizing internal defects based on methods of ultrasonic nondestructive testing, is presented. This model has a small size, which is 3.8 million parameters. Its simplicity and versatility provide high-speed learning and a wide range of applications in the class of related problems. The presented results show a high degree of information content of the ultrasonic response and its correspondence to the real form of an internal defect located inside the test object. The effect of geometric parameters of defects on the accuracy of the neural network model is investigated.

Discussion and Conclusion. The results obtained have established that the proposed model shows a high operating accuracy (F1 > 0.95) in cases when the wavelength of the probe pulse is tens of times less than the size of the defect. We believe that the combination of the proposed methods in this approach can serve as a good starting point for future research in solving flaw defection problems and inverse problems in general.

Keywords: ultrasonic nondestructive testing, defect, ultrasonic response, convolutional neural networks.

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Introduction. In the paper, the authors investigate the possibilities of using neural network technology in solving inverse problems of mechanics, in particular, in the problem of two-dimensional visualization of internal defects. These methods are widely used in medicine, civil engineering, nondestructive testing and other fields.

Thus, in [1], a system was developed for detecting cracks in steel structures and assessing their depth based on two-dimensional images. The work objective is to develop an affordable and user-friendly control system instead of expensive measuring devices. A training strategy and several neural network structures were proposed. In process of training, the average intensity of the profiles of two-dimensional steel cracks was fed into the neural network along with the maximum depth of steel cracks measured using a laser microscope. The average error of the neural network is 18 % in the test sample, which is better in comparison to the previous studies of the authors. Improving the quality of determining the depth of defects is achieved through the use of a new training strategy and a tool for assessing the crack depth.

In [2], some deep learning methods were proposed for detecting defects in the images obtained through nondestructive testing. To apply such approaches, labeled data of images with defects is needed. The authors propose a deep-transfer learning model for extracting signs of internal defects on X-ray images of composite materials of the aviation industry. The method of automatic detection of inclusion defects on X-ray images was investigated using the proposed model. The experimental results show that the model can achieve a classification accuracy of 96 % (F1 metric) with satisfactory detection results.

In [3], a method for reconstructing and visualizing internal defects in the form of a three-dimensional image using an economical and fast pulse thermography technology is proposed. A new method of rapid assessment of the depth and thickness of the defect simultaneously based on a single one-sided check is presented. The feasibility and effectiveness of the proposed solution is demonstrated through examining composite and steel samples with semi-enclosed air gaps. For a composite sample, this method can provide a relatively low, within 10%, average relative error of the estimated total volume of 3D defects.

Paper [4] considers the main causes of failure of engines of solid-fuel rockets. Peeling at the propellant /sleeve /insulation interface is a critical moment for the integrity of the engines. Modern solutions are usually limited to methods of assessing the integrity of the design of rocket engines and visual inspection of their components.

This paper presents an improved algorithm for detecting sleeve surface defects that can disrupt the bond between solid rocket fuel and insulation. The use of local binary patterns (LBP) provides a structural and statistical approach to analyzing the texture of engine image samples. The neural network analyzes the engine image samples and classifies each pixel into one of three classes: serviceable, foreign object and defect. Several tests were conducted with varying different parameters to find the optimal configuration of the neural network. As a result, the best classification accuracy was obtained for the corresponding classes: 99.08 %, 90.66% and 99.48 %.

Paper [5] provides a brief overview of artificial intelligence algorithms applicable to nondestructive testing. It focuses on two methods: artificial neural networks and fuzzy logic. Selected examples of the application of these methods in digital radiography and the eddy current method are given.

In [6], the author explores the potential of deep learning methods for electromagnetic inversion. This approach does not require calculating the gradient and gives results immediately after training the network. Deep neural networks based on a fully convolutional architecture are trained on large sets of synthetic data obtained through full three-dimensional modeling. The method effectiveness is demonstrated on models of great practical importance, representing the scenario of monitoring the electromagnetic field of carbon dioxide accumulation underground with a controlled source on the surface.

Previously, the authors investigated some problems that combine modern methods of deep machine learning and well-proven classical approaches to identifying defects [7−9].

In this paper, a neural network model is considered as a pilot study, on the basis of which a two-dimensional acoustic visualization of internal defects is carried out. A trial model of nondestructive ultrasonic testing is constructed, on the basis of which a complex of numerical experiments is carried out. The results of these experiments serve as the basis for training a neural network and its validation.

Materials and Methods. A method for identifying and visualizing internal defects based on ultrasonic nondestructive testing and a generative neural network model is proposed. An ultrasonic signal received at the internal points of the control object is fed to the input of the convolutional neural network. At the output, an image is generated that visualizes an internal defect. The inner part of the steel plate was chosen as an object to demonstrate the possibility and prospects for the development of this research method. There may be a defect inside the strip, indicated by the lack of material. The shape, size and orientation of the defect may vary. The approach involves conducting a series of numerical experiments, on the basis of which it is possible to train a deep neural network model. A training set is created for each case through varying the geometric parameters of the defect and modeling the propagation of an acoustic ultrasonic wave. It is possible to build an optimal structure of a neural network model and train it on the basis of the collected data.

Finite difference-time domain method. This method was proposed by Kane Yee [10] and belongs to the class of grid methods for solving differential equations. At the moment, this method is widely used — from tasks of geophysics to solving problems in the optical range, as well as in a number of problems of modeling media with both dispersed and nonlinear properties. The finite difference-time domain method in the acoustic formulation is used to simulate the propagation of sound in fluid media, such as air or liquids. However, in some cases, to simplify the solution of problems, this method can also be used in elastic media. Within the framework of this method, the velocity and acoustic pressure of the particles of the simulated object are arranged alternately in the grid nodes. Then their values are calculated sequentially, which provides calculating the propagation of the sound field over time.

The basic equation of this acoustic model in a flat formulation is the following:

$$\frac{\partial p}{\partial t} = -k\left(\frac{\partial v_x}{\partial x} + \frac{\partial v_y}{\partial y}\right) \frac{\partial v_x}{\partial t} = -\frac{1}{\rho}\frac{\partial p}{\partial x}, \qquad \frac{\partial v_y}{\partial t} = -\frac{1}{\rho}\frac{\partial p}{\partial y},$$

where p — pressure, v — velocity, k — volume modulus of elasticity, ρ — density of the medium.

The values of the spatial Δx and timing Δy resolutions affect how accurately and steadily the acoustic field will be calculated. These values cannot be set independently and must be selected taking into account each other.

First of all, you need to set value Δx based on accuracy considerations. At the same time, accuracy and stability are independent of each other. The simulation can be stable, but with low accuracy in the case of a coarse grid. The accuracy of the solution by this method depends on many factors. In this case, values Δx and Δy can be set as:

$$\Delta x = \frac{\lambda_{min}}{10} \sim \frac{\lambda_{min}}{20}, \Delta t \leq \frac{1}{\sqrt{d}}\frac{\Delta x}{c_{max}},$$

where λ_{min} — the wavelength that propagates in the simulated space, c_{max} — the largest value of the speed of sound in the simulated environment, d — the dimension value, for a flat problem $d = 2$.

A reference model of acoustic ultrasonic wave propagation is constructed in the COMSOL package. Accordingly, the solution is carried out by the finite element method and the finite difference method. Figure 1 below shows the normalized acoustic pressure values read at the model point. The model is a square area made of steel with a hole inside. Small differences in the signal shape are due to the way the source of ultrasonic vibrations is set. In the case of FEM — points are on the circle, in the case of FDTD — a point is in the grid node.

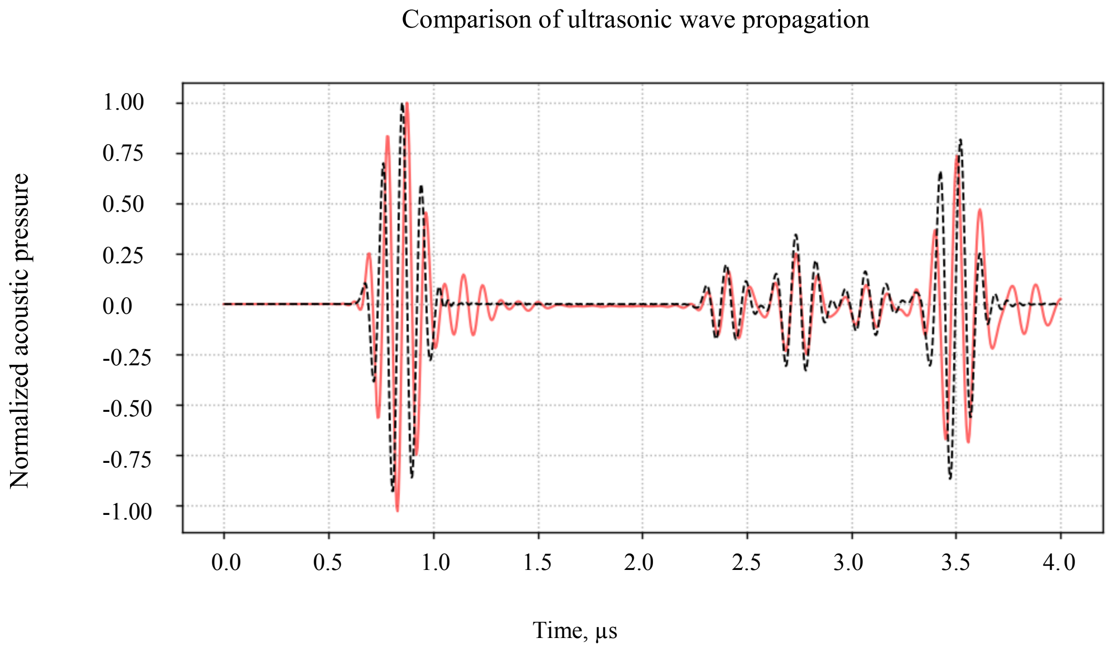


Fig. 1. Shape of the direct and reflected ultrasonic signal. The dashed line shows the values calculated using the FDTD method, the solid line shows the values calculated using the FEM

Since the grid has a limited size, it is not possible to simulate the propagation of acoustic waves outside this area, so special boundary conditions are applied. Moore's Absorbing Layers or Perfect Matched Layers (PML) are used [11]. These conditions reduce significantly the reflectivity of the boundaries of the area in which the simulation takes place and create the effect of waves passing beyond the boundaries of this area.

Nondestructive testing model. The inner part of the steel plate containing the defect was chosen as a trial model of nondestructive testing. The study area size is 20×20мм. Defects are presented in the form of geometric shapes: ellipse, triangle, square, rectangle. Physical parameters of the defects vary relative to the simulated area within the following limits: the location of the defect — from 0.3 to 0.7; the size of the defect — from 0.1 to 0.35; the angle of defect inclination — from 0° to 360°. The input signal consists of a fixed number of discrete values specified by the experiment time. The time of the experiment was chosen in such a way that the probing pulse, having reflected from the defect, could cover the distance and return to the point of the initiating signal. The probing pulse frequency is 10 MHz.

Figure 2 shows the scheme of the numerical experiment. The defect is located in the center of the probed area with a given offset. The source of the ultrasonic signal is shown with red mark. The signal reading points are shown with green marks. The broken line shows the boundaries of the defect.

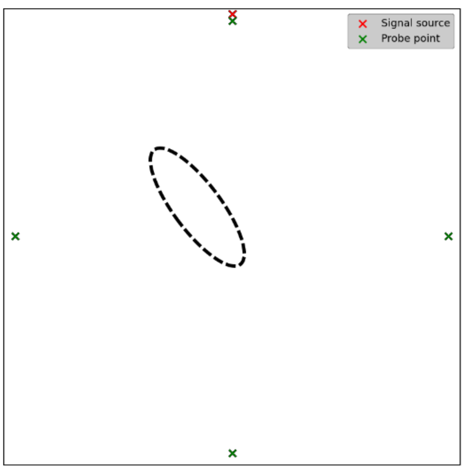


Fig. 2. Scheme of one of the conducted numerical experiments

The model provides evaluation of the possibility of using the proposed method and the further prospects for its application. The ultrasonic signal is set at the internal point of the control object. The points that simulate sensors that read the transmitted and reflected signals are located on different sides of the supposed location of the defect. Such a virtual model enables to evaluate the effect of some experimental parameters on the neural network quality. Based on the implemented approach, it is possible to build models that reflect real technical tasks. Figure 3 shows the propagation and reflection of an ultrasonic wave from a defect inside the study area.

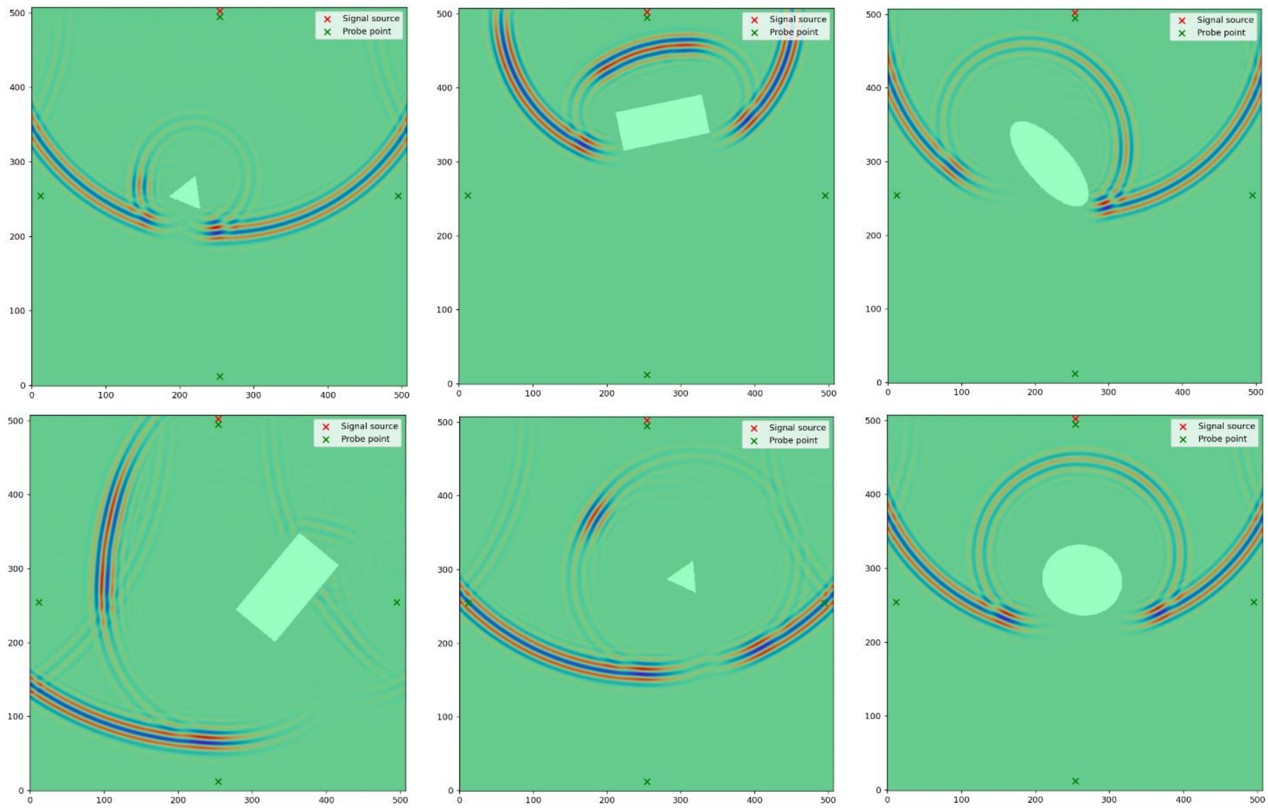


Fig. 3. Propagation of an ultrasonic wave and its reflection from various defects

Neural network model. Convolutional neural networks (CNN) are a special neural network tool for processing data with a grid structure (two-dimensional images, one-dimensional signals) [12]. At the moment, it is one of the most rapidly developing and promising deep learning tools [13−15].

They have also proved extremely successful in other practical applications, including video analysis and time-series data processing (the latter can be considered as a one-dimensional grid that processes samples at fixed time intervals). CNN is a key example of the successful application of ideas obtained under studying the brain (to some extent inspired by the structure of the mammalian visual system). As the name suggests, the convolutional network uses the convolution operation, i.e., filtering using a feature map or kernel, instead of the general matrix multiplication in fully connected networks (in fact, convolution corresponds to the product of a sparse matrix).

To solve the problem of defect visualization, the authors suggest using a convolutional neural network model. An ultrasonic signal received at the internal points of the control object is applied to the input of the model. The output generates an image with the expected shape, location and orientation of the defect. The input signal passes through layers of one-dimensional convolution (Conv1D) and subsampling (MaxPooling). After that, the data falls on a fully connected layer. This convolutional part of the network is used to extract features from the signal, on whose basis the defect will be visualized. The second part of the network generates images corresponding to the shape, location and orientation of the defect. Data from a fully connected layer is transformed and displayed on a two-dimensional layer. From this layer, after passing through a number of trained unfolding layers (Conv2D Transpose), the final image is obtained, which visualizes the internal defect. The model of the convolutional neural network used in this work is

shown in Fig. 4. Under each layer, the size of the input data and the number of convolution kernels are shown. For example, 504×32 means that 504 values are fed to this layer and 32 different convolutional filters are applied to them.

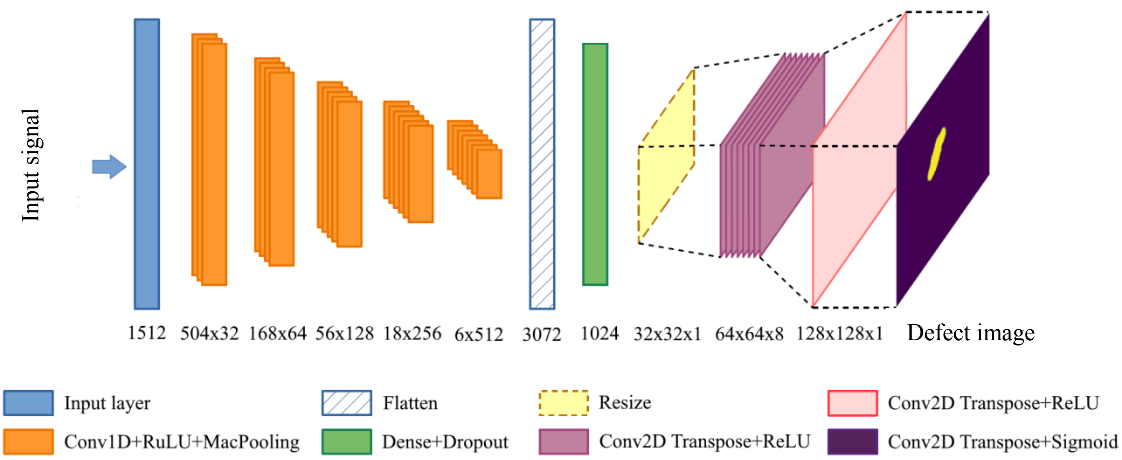


Fig. 4. Architecture diagram of a convolutional neural network

Model training and validation. Within the framework of a complex of numerical experiments, 17,000 problems with various geometric parameters of the defect were solved. 14,000 samples were used for training, 2,000 — for testing and 1,000 — for validation.

In training, the success rate is the training error. When checking the operation of a neural network model on test data that was previously unavailable to the network, its ability to generalize is determined. During the testing process, the testing error is calculated. Thus, the model performance can be judged by two key factors. The first is to achieve the smallest learning error. The second is to reduce the difference between the training and testing error.

There are several regularization techniques in the machine learning. When training neural networks, one of the problems is overtraining. It is expressed in the loss of the ability to generalize in the learning process. One of the most popular methods of preventing it is the use of Tikhonov regularization (ridge regression or L2), also called weight decay in machine learning.

One of the important stages of training a neural network model is the initialization of weights. One of the currently popular initialization methods is the Xavier method [16]. This method simplifies the signal transmission in case of forward and backward propagation of an error through the network layers. The method is suitable for both linear and sigmoid activation functions (its unsaturated section has a linear character).

The batch-normalization method was proposed by Ioffe and Szegedy [17]. During the propagation of the signal through the network layers, its distortion can occur both in terms of mathematical expectation and variance (this effect is known as an internal covariance shift). This may cause some discrepancy between the gradients at different network levels.

General regularization approaches are used when training a neural network model. The simplest of them are early stopping and the use of the dropout technique. These methods provide more stable training of the model. Due to the sufficient size of the training sample and the complexity of data augmentation, the latter is not performed.

As part of this work, the data set is not balanced. Below, in Fig. 5, you can see the distribution of defects depending on their size.

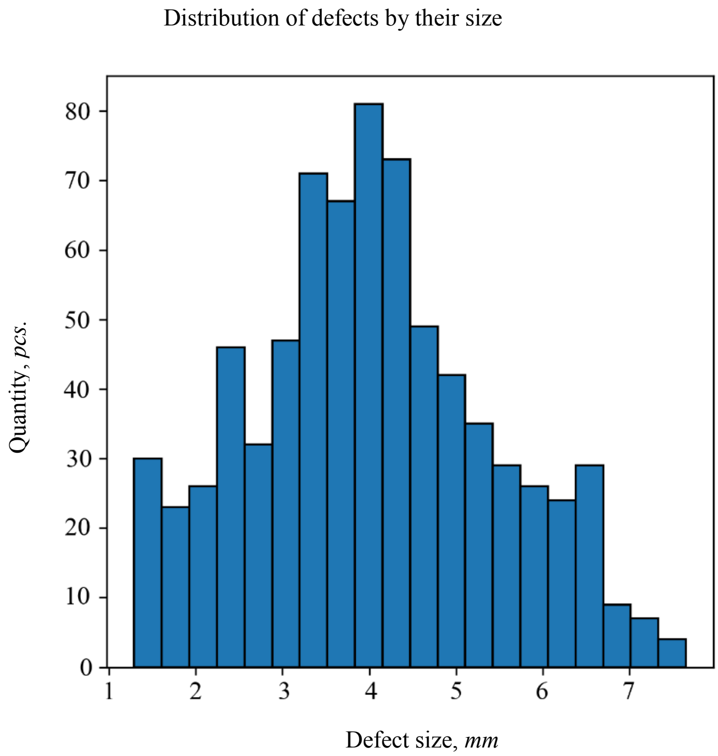


Fig. 5. Number of defects depending on their size in the training data set

Training a neural network is the equivalent of solving an optimization problem in which the minimum of the loss function is searched for. This function shows how well the model performs its task. The correct selection of the loss function has a great impact on the learning outcome. In this problem, the optimal choice is to use the Jaccard similarity coefficient (Intersection over Union). This factor is often used in computer vision problems and is defined as:

$$IoU = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|}$$

Accordingly, the loss function is defined as $1 - IoU$ and reflects the difference between the two samples. It is also known as the Jaccard distance. Also, to assess the quality of the neural network model, metric $F1 = \frac{2 \times IoU}{IoU+1}$ is used, which reflects the harmonic mean between completeness and accuracy.

One of the most popular Adam algorithms [18] is used for training. The authors used the open TensorFlow library and the Keras framework. These software solutions include the majority of modern algorithms and models. It took 200 training epochs to achieve an acceptable level of the model performance.

Research Results. The use of a neural network approach to solving inverse problems has long proven itself [8, 19−20]. With the development of machine learning and the emergence of new techniques, new methods of data interpretation become available, and new opportunities for solving classical problems of mechanics and flaw detection appear.

The authors have presented a convolutional neural network model developed to solve the problem of visualization of internal defects based on methods of ultrasonic nondestructive testing. This model has a small size, which is 3.8 million parameters. Its simplicity and versatility provide high-speed learning and a wide range of applications in the class of related problems. The authors use the FDTD method for simulating the propagation of ultrasonic waves and compare its results with the results of the finite element method. The selection of this method made it possible to significantly increase the speed of calculating models, compared to the tasks solved earlier [21].

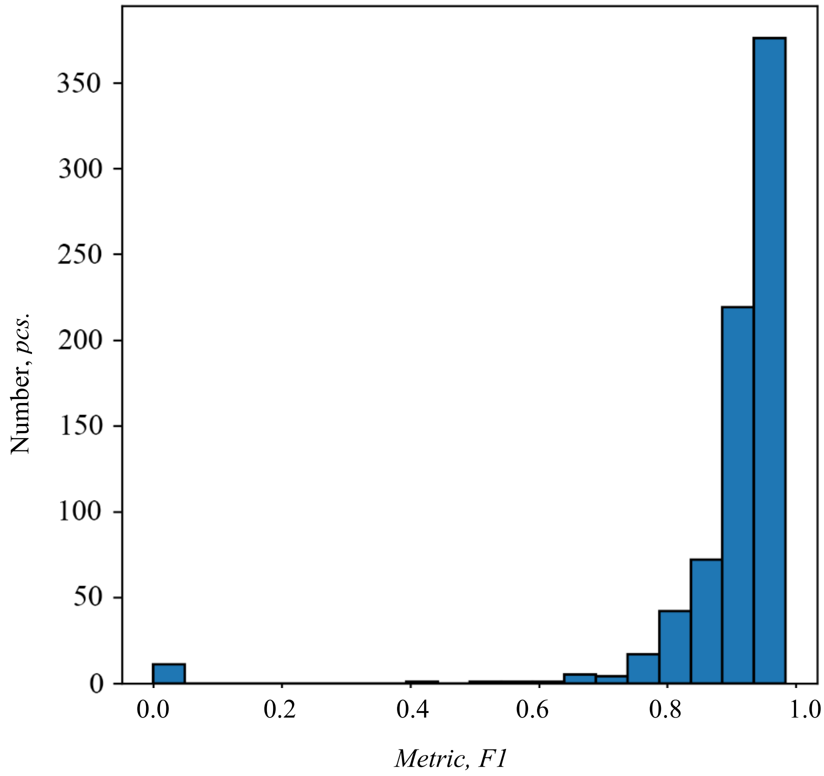


Fig. 6. Number of identified defects with a certain accuracy

After training the neural network model, its operation is validated on the corresponding data set. Metric F1, described above, is used to evaluate the overall performance of the model. In general, the accuracy of the proposed method is at a high level. The average value of F1 factor for the entire validation sample is 91 %. Figure 6 shows that some of the defects were not identified by the neural network model.

In Fig. 7, you can see how accurately the neural network model performs visualization of defects of various sizes. Visualization was performed on a validation data set.

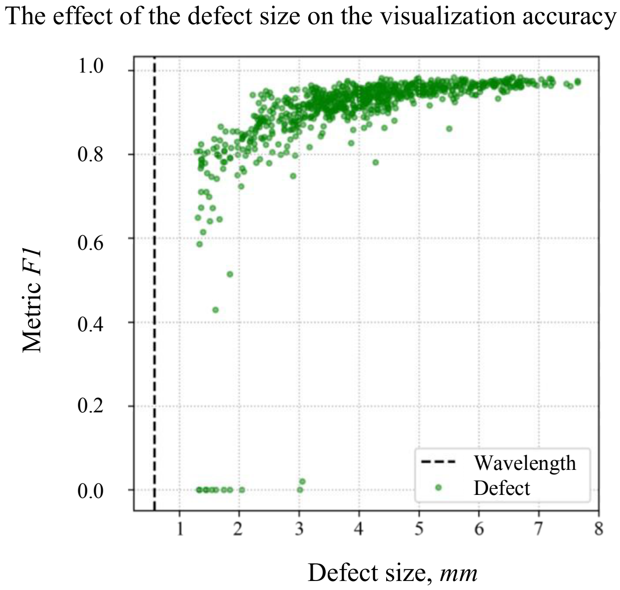
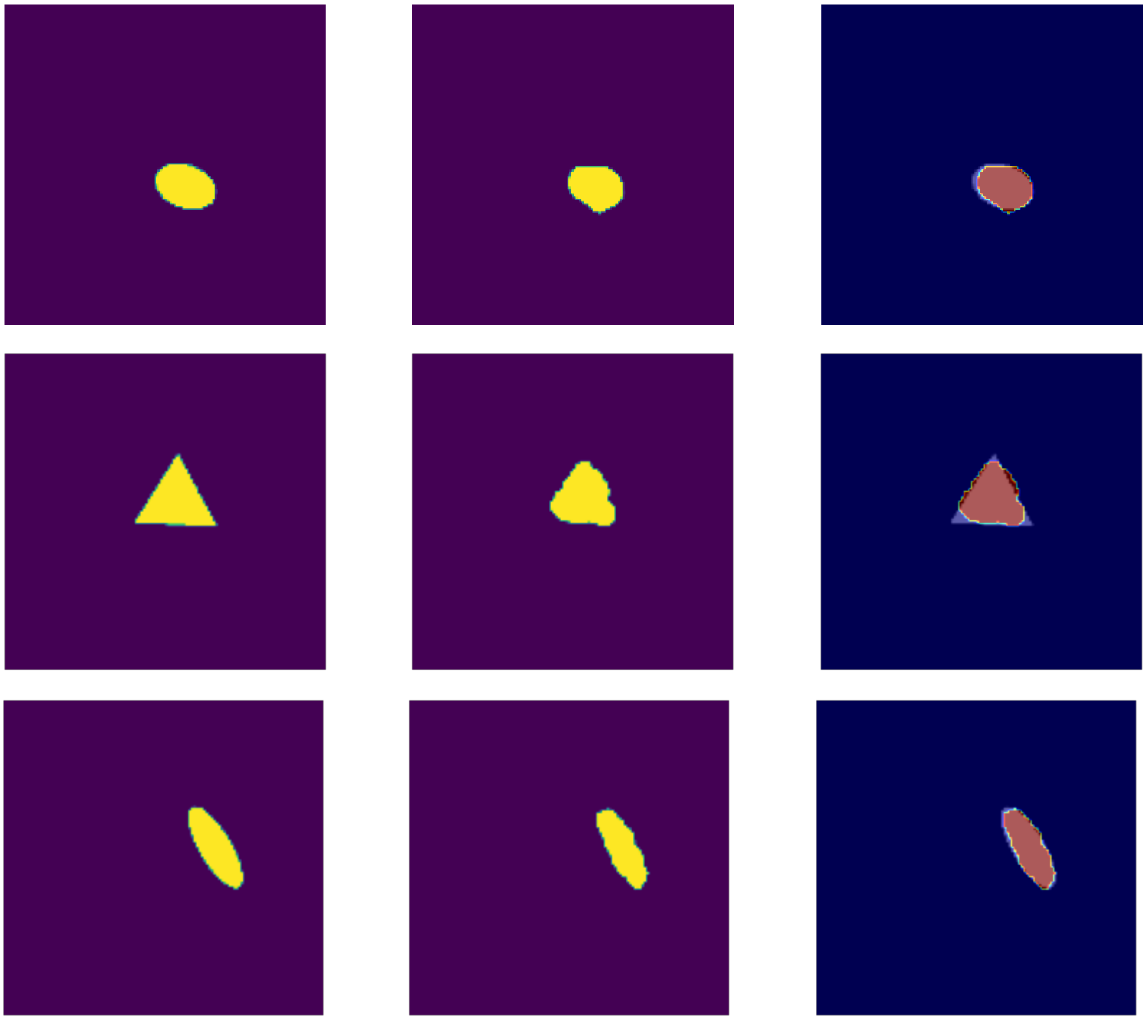


Fig. 7. Dependence of the visualization accuracy on the defect size

Figure 8 below shows the results of the neural network model operation. The images show the location, boundaries and shape of the alleged defect.



a) *b*) *c*)

Fig. 8. The result of visualizing the defect with a neural network: a) original defect, b) defect visualization based on the ultrasonic response, c) difference between the original and restored samples

Discussion and Conclusions. In this paper, the potential of using machine learning methods in the problem of ultrasound imaging is shown. The authors have built a test model of nondestructive testing. Based on this model, a data set is prepared for training a neural network. A convolutional neural network model is proposed that provides predicting the shape, location and orientation of defects inside a solid body. The results obtained show a high degree of informativeness of the ultrasonic response and its correspondence to the real form of the internal defect.

Based on the results obtained, it is revealed that the proposed model shows high accuracy of work ($F1 > 0.95$) in cases when the wavelength of the probing pulse is ten times smaller than the size of the defect.

The authors believe that the combination of the proposed methods in this approach can serve as a good starting point for future research under solving problems of flaw detection and inverse problems in general.

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Claimed contributorship

P. V. Vasiliev: basic concept formulation; research objectives and tasks. A. V. Senichev: computational analysis; text preparation; formulation of conclusions. I. Giorgio: the text revision; correction of the conclusions.

All authors have read and approved the final manuscript.